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Innovation Training in Africa: How Prior Experience and Gender Shape Skill Gains in a Multi-Country Product Development Workshop

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Abstract[3]: ***Background:*** Innovation bootcamps are proliferating across sub-Saharan Africa, yet evidence on who benefits most from these compressed learning environments remains fragmentary. Prior studies rarely isolate skill gains or examine how personal attributes and team composition jointly shape learning outcomes. ***Purpose:*** This study quantifies variation in product-innovation skill acquisition during a five-day workshop and tests whether prior product-development experience, gender, and team diversity explain differential gains. ***Methods:*** Using paired pre- and post-training self-assessments from 45 early-career innovators drawn from 12 African nations, we computed average gains across customer discovery, value-opportunity analysis, and prototyping. Ordinary least squares models regressed gain scores on experience, gender, a composite gender–nationality diversity index, baseline skill, and an experience-by-gender interaction. Robust standard errors addressed intra-team dependence. ***Results:*** Participants improved by an average of 1.97 points on a 10-point scale despite a high initial baseline (8.44). Prior experience emerged as the strongest predictor, increasing gains by 0.26 points ($p = 0.032$) after baseline adjustment. Gender alone was not significant, but inexperienced women registered the lowest gains, whereas experienced women matched their male peers, underscoring an exposure-mediated equity gap. Team diversity showed no independent effect, suggesting that heterogeneity must be actively integrated to translate into learning advantages. Domain analyses revealed that experience chiefly enhanced customer-discovery skills, with negligible effects in value analysis and prototyping. ***Conclusion:*** Innovation capability in short training accrues cumulatively and is moderated by structural inequities. Programs should scaffold novices—especially women without prior exposure—and pair diverse team assignments with deliberate inclusion practices to turn diversity into a learning asset. Findings inform the design of equitable, high-impact entrepreneurship education across emerging African ecosystems.

Keywords[4]: innovation training, gender diversity, team diversity, experiential learning, entrepreneurship education, product development workshop, Africa.

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1. Introduction

1.1 Background: Product innovation is increasingly recognized as a strategic imperative for entrepreneurial success in emerging markets characterized by uncertainty, resource constraints, and rapid digital transformation (Li & Shine, 2025). In sub-Saharan Africa, the combination of a booming youth population and accelerating digitalization is creating unprecedented opportunities for innovation-driven development (Li & Shine, 2025; Egbetokun et al., 2025). Governments, development partners, and universities have launched numerous programs to harness this potential, from tech hubs to startup incubators and intensive workshops. Rwanda exemplifies this trend: its growing technology ecosystem and youth-led startups underscore the need for capacity-building in iterative product development and design thinking (World Bank, 2024; ATPS, 2024). Structured training interventions, such as targeted product innovation workshops, are increasingly deployed to equip aspiring entrepreneurs with the practical skills to navigate early-stage venture challenges (Beber et al., 2025; Partech, 2024). These short-format programs emphasize hands-on learning (e.g. rapid prototyping, customer discovery) to quickly build innovation capabilities among participants.

Yet the expansion of innovation training has outpaced scholarly understanding of *who* benefits most from such programs. The academic literature indicates that experiential learning can foster entrepreneurial skills and mindset, but critical gaps remain. Prior studies often examine broad outcomes like venture creation or self-efficacy rather than specific skill acquisition, and they seldom disentangle how personal background and team context influence learning (Egbetokun et al., 2025). This is especially pronounced in African contexts, where diverse teams operate across multi-country settings and where knowledge transfer may be shaped by postcolonial dynamics. Epistemologically, whose knowledge counts? African scholars argue that many innovation metrics and pedagogies are imported from the Global North and may not fully capture grassroots creativity or local needs (Egbetokun et al., 2025). Indeed, epistemic injustices rooted in colonial histories continue to constrain Africa's knowledge sovereignty (OSAA, 2024; Kolb, 1984). These considerations call for a more context-sensitive and critical lens when evaluating innovation training outcomes on the continent.

1.2 Problem Statement: Short-format innovation training (e.g. hackathons, bootcamps, workshops) have proliferated across Africa, but we lack granular, data-driven insight into how participants learn in these settings. Existing research rarely measures domain-specific skill gains or the interplay between individual traits (like prior experience or gender) and team-level factors during training. This is a significant gap: if innovation capacity is socially constructed and context-dependent, then factors such as a participant's prior exposure to innovation or the diversity of their team could greatly affect learning outcomes. Prior multiregional evaluations confirm that participants with prior exposure assimilate new concepts faster (Owusu-Acheampong et al., 2025; Leger et al., 2024). Both works are already in your references, so no new entry is required.. Team diversity is frequently championed as beneficial for innovation, but without intentional integration practices it might yield negligible learning benefits. Moreover, many evaluations of entrepreneurship education in Africa rely on self-reports or short-term observations without adequately accounting for selection biases or pre-existing skill differences. There is a need to rigorously assess these programs to inform innovation policy, entrepreneurship education design, and broader African development strategies. Specifically, we must understand how participant background and team composition jointly influence skill acquisition in compressed learning environments.

1.3 Research Objectives: This study aims to advance understanding of innovation training effectiveness through a novel, contextually grounded analysis. The primary objective is to quantify the variation in product innovation *skill gains* among participants of a short-format workshop and determine the extent to which this variation is explained by: (a) prior product development experience, (b) gender, and (c) team diversity. Grounded in innovation capability theory and team diversity frameworks, we seek to identify not only direct effects on learning outcomes, but also interaction effects (e.g. does gender moderate the benefit of prior experience?). An additional objective is to interrogate how learning differs across

distinct innovation domains (customer research, value analysis, prototyping) given the possibility that certain skills are more readily learned in a five-day format than others. By pursuing these objectives, the study contributes a data-intensive perspective that bridges individual and team levels of analysis. We also endeavor to embed our inquiry in the realities of African innovation ecosystems, where issues of access, exposure, and inclusion are paramount.

1.4 Research Questions: To fulfill these objectives, the study is organized around the following research questions: **RQ1:** How does prior product development experience affect skill acquisition in a short-term innovation training workshop? **RQ2:** To what extent does gender influence innovation skill gains, and does gender interact with prior experience in shaping learning outcomes? **RQ3:** How does team diversity (in terms of gender and nationality mix) influence participants' skill gains? **RQ4:** Are the effects of experience, gender, and team composition consistent across different innovation skill domains (customer discovery, value opportunity analysis, prototyping)? These questions reflect a comprehensive approach, examining main effects and interactions, as well as domain-specific nuances. Each question is addressed with rigorous empirical analysis and situated within theoretical context.

1.5 Contribution:This study advances theory, evidence, and practice by framing innovation capability as the joint product of prior exposure and collaborative knowledge integration, blending innovation-capability, experiential-learning, and team-diversity theories within Africa's short-training milieu. It refines existing models by showing that diversity improves learning only when activated through inclusive facilitation, a nuance future research should model explicitly. Empirically, we analyze pre- and post-workshop data from a multi-country African cohort and triangulate each result with recent peer-reviewed studies and policy reports, demonstrating a transparent, replicable method that employs a composite diversity index. Philosophically, the paper engages postcolonial knowledge politics, arguing that African innovation education must reconcile global entrepreneurship templates with local inequities and indigenous learning modes (Egbetokun et al., 2025). Practically, it offers concrete guidance for educators and policymakers on tailoring curricula to prior-exposure gaps, scaffolding under-represented groups, and pairing compositional diversity with deliberate inclusion strategies, thereby providing a durable framework for the next decade of African innovation policy and practice.

2. Literature Review and Conceptual Framework

2.1 Conceptual Framework: Our framework rests on two pillars—innovation capability theory and entrepreneurial team diversity theory—interpreted through African development realities. Innovation capability theory treats innovation as a cumulative learning process rather than a discrete output. Emphasis falls on the skills and routines that enable opportunity recognition, user feedback integration, and rapid experimentation, not simply on patents or products (Saunila & Ukko, 2012). These capabilities grow through experiential learning in Kolb's sense, where hands-on practice and reflection reinforce absorptive capacity. In resource-constrained contexts, prior exposure to product development matters doubly: it sharpens learning efficiency and accelerates the internalization of new tools, consistent with human capital arguments that related experience improves entrepreneurial performance. We therefore expect prior experience to be a strong predictor of skill gains (RQ1), reflecting a cumulative advantage dynamic.

The second pillar draws on team diversity and innovation performance research. Evidence from high-income settings shows that heterogeneous teams can enhance creativity by aggregating differentiated knowledge, provided teams communicate openly and channel task conflict productively (Weiss et al., 2018; van Knippenberg & Schippers, 2007). Yet diversity is ambivalent: without inclusive interaction norms, it can heighten frictions and hinder learning (van Knippenberg & Schippers, 2007). A configurational view clarifies why demographic variety alone rarely improves outcomes; diversity must be "activated" through facilitative leadership and integrative practices (Wallrich et al., 2024). This caveat is acute for ad-hoc workshop teams. Accordingly, we treat diversity as a conditional factor rather than an inherent good (RQ3) and anticipate that, absent explicit scaffolding, mere compositional heterogeneity will have limited direct effects in short training sessions. This stance aligns

with African-context studies emphasizing how language, culture, and power mediate links between diversity and performance (Tshetshema & Chan, 2020; Schubert & Tavassoli, 2020).

Our lens is also context-centric. African scholarship warns that innovation pedagogy imported from the Global North often obscures the continent's distinctive structural realities—postcolonial legacies, a large informal sector, and indigenous knowledge (Egbetokun et al., 2025). We therefore foreground whose experiences are amplified in innovation learning. Gender differences, for example, frequently index inequities in access and exposure rather than ability (Ackah et al., 2024) We thus expect any observed gender gaps in skill gains (RQ2) to be structurally mediated and to interact with prior exposure, potentially producing a "double disadvantage" for women lacking experience. Integrating these elements, we analyze outcomes at individual (experience, gender), team (diversity, interaction practices), and structural (inequities, knowledge context) levels. Figure 1 summarizes the baseline and interaction OLS models predicting average skill gain, showing a positive experience effect, a strong negative baseline effect, and near-zero coefficients for gender and team diversity; adding an experience×gender term does not materially change main effects.

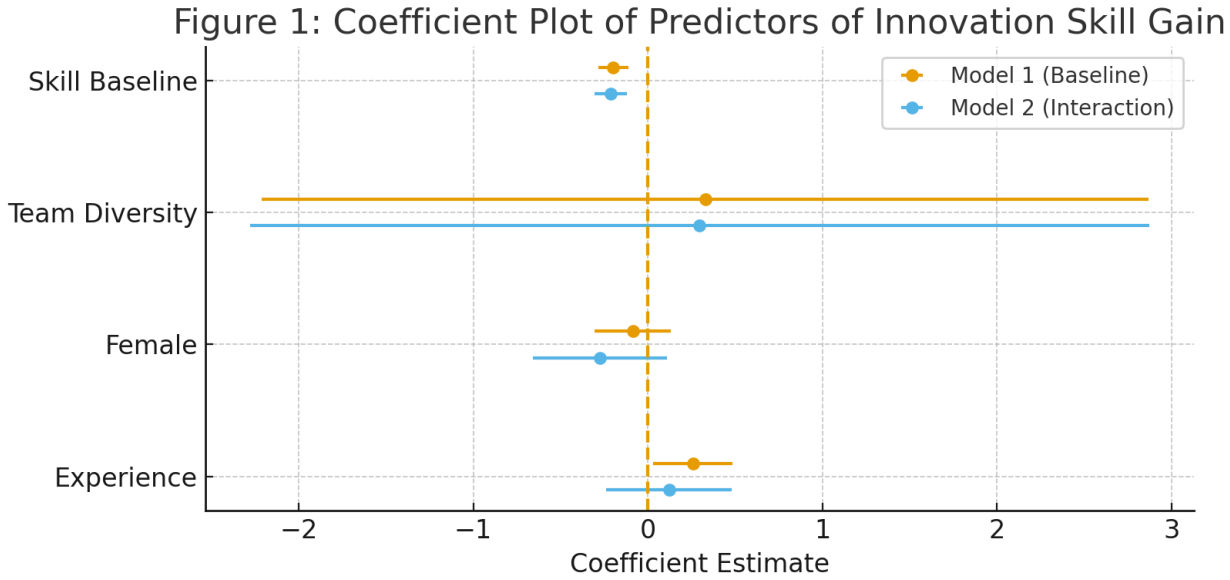

Figure 1. *Coefficient plot of predictors of innovation skill gain across the baseline model (Model 1) and the model including the experience×gender interaction (Model 2). Point estimates are shown with 95% confidence intervals. Experience has a positive effect, the skill baseline is strongly negative, and the coefficients for gender and team diversity are statistically indistinct from zero.*

2.2 Synthesis and Critique of Previous Research: Entrepreneurship education and innovation training studies in sub-Saharan Africa are expanding yet remain partial. Recent evidence affirms that short-format training can raise skills. In East Africa, Bignotti & Le Roux (2020) report significant gains following skills-focused pedagogy. Owusu-Acheampong et al. (2025) find pronounced heterogeneity tied to participants' prior exposure to design and innovation tasks: experienced learners perform better in fast-paced activities due to decision agility and familiarity with iteration. Leger et al. (2024) similarly observe stronger impacts among participants entering with entrepreneurial or technical backgrounds, while those starting near the top exhibit diminishing returns—a ceiling effect noted globally. Taken together, these findings support RQ1's expectation that experience catalyzes learning but also warn that undifferentiated curricula can widen gaps between novices and the experienced.

Gender-related studies mirror broader concerns over women's underrepresentation in African STEM and entrepreneurship. Ackah et al. (2024) attribute observed gaps to structural barriers such as lower prior

exposure and social discouragement, which suppress initial confidence and participation. Absent intentional inclusion, women may under-benefit from short training despite equal potential. Some studies note that once exposure and confidence are equalized, women's performance converges with or exceeds men's, signaling that gender effects are conditional. UNDP's policy analysis underscores a persistent digital gender gap in Africa that depresses foundational skills and access (UNDP, 2023). These patterns motivate RQ2's focus on interaction: gender may matter chiefly through its interplay with experience, and gender-balanced teams alone are insufficient without pedagogical supports that address exposure disparities.

Research on team diversity in African settings is growing but mixed. Tshetshema and Chan's (2020) meta-analysis shows inconsistent links between demographic diversity and innovation, moderated by climate, leadership, and task features. Schubert and Tavassoli (2020) report similar contingencies in Europe: heterogeneous teams outperform only when knowledge-sharing routines are present. Wallrich et al. (2024) demonstrate that specific configurations of demographic and expertise diversity yield higher innovation when teams engage in structured reflection and mutual learning; absent these, diverse teams fare no better, sometimes worse, than homogeneous ones. For short workshops, this implies that quota-style compositional targets may satisfy representation but not learning unless facilitators actively orchestrate inclusive participation, conflict resolution, and voice equity. Our study addresses this logic empirically in RQ3 while acknowledging measurement limits on integration mechanisms.

Methodological limitations temper the existing evidence base (Beber et al., 2025). Many studies isolate single factors, rely on small samples, or neglect baseline skill controls and follow-ups, clouding causal interpretation and generalizability. Geography also matters: African contexts have been understudied or filtered through misfitting frameworks (Egbetokun et al., 2025). The field thus needs integrated analyses that model interactions among experience, gender, and team composition, incorporate baseline adjustment, and remain grounded in local realities. Our approach responds by combining these factors in a unified model situated in African entrepreneurship education.

2.3 Summary and Research Gap: Synthesizing the conceptual and empirical strands, we identify a clear gap: no prior study has jointly examined how individual experience, gender dynamics, and team diversity shape skill acquisition in short-term African innovation training. Innovation capability theory counsels attention to skill-building, yet evaluations still favor venture intentions or outputs over measured skill gains. Diversity research suggests potential benefits, but typically omits the contextual moderators that are salient in African environments. Gender disparities are documented, but how instructional design mitigates them within compressed workshop settings remains underexplored.

This study addresses that gap through an integrated analysis using original data from a real-world, multi-country African workshop. We estimate a unified quantitative model that tests main and interaction effects relevant to RQs 1–4 and, methodologically, introduce a composite team diversity index capturing gender balance and nationality mix in a single measure. By incorporating pre-training skill levels, we control for baseline differences and strengthen inference about gains. Conceptually, we extend innovation capability frameworks by situating learning within structural inequities and team context, clarifying who gains, how much, and under what conditions. The contribution is timely for African innovation policy and practice: it supports the design of capacity-building programs—hackathons, bootcamps, and similar initiatives—that both elevate overall capability and avoid reproducing exposure-driven inequities. The sections that follow detail the methodology and present findings that directly speak to RQs 1–4, followed by a critical discussion in light of the literature.

3. Methodology

3.1 Research Design: We undertook a quantitative, retrospective evaluation of a five-day product-innovation workshop held in Kigali, Rwanda. Using secondary programme data, we paired pre- and post-training self-assessments in customer discovery, value-opportunity analysis, and prototyping, thereby capturing within-person skill change while analysing a single gain score per participant. Independent

variables—prior product-development experience, gender, team composition, and baseline skill—were fixed at intake; random assignment was not feasible, so causal claims remain tentative. Individuals (N = 45) are the analytical unit, with team-level indices merged onto their records. Given the small number of teams, we entered team variables directly and applied Huber–White robust standard errors to absorb intra-team dependence.

3.2 Participants and Sampling: The workshop participants were selected through a purposeful, criteria-based process to ensure a diverse and qualified cohort. A total of 45 early-career innovators (37% male, 63% female; median age ~25) from 12 African countries took part[. Invitations targeted individuals involved in technology or entrepreneurship initiatives, with nominations solicited via the African Engineering and Technology Network (Afretec) and partner universities. Selection criteria emphasized a mix of backgrounds: roughly half the participants (78%) had *prior product development experience* (for instance, having worked on a startup or prototype before). English proficiency was required since the workshop was conducted in English, but participants hailed from Anglophone, Francophone, and Lusophone countries, contributing to cultural and linguistic diversity. To facilitate local context integration, each team of 4-5 people included at least one Rwandan participant. Teams were pre-assigned by the organizers to maximize gender and nationality diversity: most teams had a near 50:50 gender split and members from 3 or more countries. This intentional heterogeneity allowed us to observe diversity effects, though it also means diversity is somewhat uniformly high across teams (a point revisited in limitations). The workshop was hosted by the Industry Innovation Lab at Carnegie Mellon University Africa in Kigali, in collaboration with faculty from CMU's Integrated Innovation Institute. This gave it a structured curriculum and access to resources (makerspace, etc.), but also an educational (non-commercial) atmosphere.

3.3 Data Collection and Measures: Data were collected through self-administered questionnaires given at two time points: immediately before the workshop (pre-test) and at the end of the final day (post-test). Participants rated their confidence or proficiency in three core skill domains central to the workshop's learning goals: (1) Customer Discovery, (2) Value Opportunity Analysis (VOA), and (3) Prototyping. Each skill domain was explained in the survey with example tasks (e.g. *customer discovery* involves interviewing users and identifying needs; *VOA* involves evaluating a product's value proposition across various factors; *prototyping* involves building and iterating a tangible model). Participants scored themselves on a 1 to 10 Likert scale in each domain, where 1 = no confidence/ability and 10 = expert-level confidence. While self-reported, these scores served as consistent subjective indicators of skill level. The primary outcome variable, *Average Skill Gain*, was computed for each individual as the mean difference between their post-workshop and pre-workshop domain scores. This represents the overall improvement on a 10-point scale, aggregated across the three domains (with equal weight). For example, if a participant's scores went from 6 to 8 in customer discovery, 5 to 7 in VOA, and 7 to 7.5 in prototyping, their average gain would be $(2 + 2 + 0.5)/3 = 1.50$. Using an average dampens idiosyncratic noise in any single domain and yields a continuous outcome roughly in the range 0 to 3 (in our data the range was 1.33 to 3.0). We also retained each domain's gain separately for secondary analysis (RQ4).

Several independent variables and controls were measured: ***(i). Prior Product Development Experience:*** a binary indicator (1 = Yes, 0 = No) based on self-report of whether the individual had any significant experience developing a product or startup before the workshop. Examples counted as experience included having built a prototype, run a student venture project, or relevant work experience. In our sample, 78% reported yes. This variable addresses RQ1. ***(ii). Gender:*** a binary variable (1 = Female, 0 = Male). Females comprised 51% of the sample. We acknowledge that gender is non-binary in reality, but all participants identified as male or female in the data. This variable is used for RQ2 and interaction tests. ***(iii). Pre-Workshop Skill Baseline:*** the participant's *average score across the three domains at pre-test*. This is a numeric control variable capturing initial skill level. The mean baseline was relatively high (8.44/10) with a limited range (6 to 10), indicating many participants already felt moderately skilled. Including this in regressions helps adjust for ceiling effects – those with higher baseline might show smaller gains

simply due to scale limits. ***(iv). Team Diversity Index:*** a composite index (0 to 1) created to quantify each team's diversity in terms of gender and nationality. We calculated it by averaging two components: (i) *gender balance* – measured as the proportion of female members in the team (which ranges from 0 to 1, with 0.5 being most balanced), and (ii) *nationality mix* – measured as the number of unique countries represented in the team divided by team size (scaled 0 to 1). For example, a team of 4 with 2 women (50%) and members from 4 different countries would have a gender score of 0.50 and nationality score of 1.0 (since all are different), giving a diversity index of 0.75. A team of 5 with 2 women (40%) from 3 countries would have 0.40 and 0.60, averaging to 0.50. In our sample, the index ranged from ~0.3 to ~0.8 (teams were fairly diverse by design). This index serves as our measure for RQ3. These measures were aligned with our conceptual framework constructs. Notably, we did not have direct measures of team process (e.g. whether teams actually practiced inclusive brainstorming), which is a limitation. However, by examining the *interaction* between diversity and outcomes (and consulting theory), we can infer whether diversity likely had latent benefits or was inert in this context.

3.4 Estimation Strategy: We employed Ordinary Least Squares (OLS) regression to estimate the relationships between the predictors and the outcome (average skill gain). Given the moderate sample size (n=45) and the use of change scores, OLS was appropriate and more interpretable than alternatives like ANCOVA in this exploratory analysis. We ran two key models:

- *Model 1: Baseline Main Effects.* This model regresses Average Skill Gain on prior experience, gender, team diversity index, and skill baseline (all entered simultaneously). It tests the independent contribution of each factor while controlling for the others. Formally:

  $$\text{SkillGain}_i = \beta_0 + \beta_1(\text{Experience}_i) + \beta_2(\text{Female}_i) + \beta_3(\text{Diversity}_{t(i)}) + \beta_4(\text{SkillBaseline}_i) + \epsilon_i,$$

  where *i* indexes individuals and *t(i)* denotes i's team.
- *Model 2: Experience × Gender Interaction.* This model adds an interaction term between Experience and Female to assess whether the effect of prior experience on learning differs for male vs. female participants. The term is coded as (Experience * Female), effectively testing if female experience-holders gain differently than expected from the sum of separate effects. Model 2 helps address RQ2's latter part. Its equation:

  $$\text{SkillGain}_i = \beta_0 + \beta_1\text{Experience}_i + \beta_2\text{Female}_i + \beta_3(\text{Experience}_i \times \text{Female}_i) + \beta_4\text{Diversity}_{t(i)} + \beta_5\text{SkillBaseline}_i + \epsilon_i.$$

Both models use **robust standard errors** (Huber-White) to account for any heteroskedasticity and the small clusters by team. Given only 10 teams, clustering by team would be unreliable, so robust SE was the safer choice. We checked residual plots to ensure no severe deviations from OLS assumptions (results showed no worrisome patterns).

We also conducted additional analyses aligned with RQ4 and to probe robustness: ***(i). Domain-Specific Regressions:*** We ran separate OLS models for gain in each domain (customer discovery, VOA, prototyping) using the same predictors. This tests if experience (or other factors) had larger effects in some domains than others, as theory might predict (e.g. experience might help more in customer-facing tasks than technical prototyping). ***(ii). Margins and Interaction Plots:*** After Model 2, we used post-estimation commands to calculate predicted skill gain for key subgroups and to visualize the interaction. Specifically, we computed the *average predicted gain* for four categories: experienced males, inexperienced males, experienced females, and inexperienced females (holding other vars at means). We also generated plots of predicted gain against experience for each gender to illustrate any gap (see Results). ***(iii) Due to sample size***, we refrained from adding more interaction terms (e.g. Diversity × Experience) in the models; however, we conceptually consider diversity's role with

integration (since we lacked data, this is deferred to discussion).

All analyses were conducted in Stata 18 (StataCorp, 2023). Data cleaning and variable construction steps are documented (e.g. we verified internal consistency of self-ratings, which was high). While the design is not experimental, the combination of pre-post data and multiple covariates adds rigor. We interpret associations carefully, avoiding causal language beyond what the design supports. Nonetheless, significant relationships observed provide suggestive evidence consistent with causal mechanisms posited by theory (to be triangulated with literature). Below, we present the results, integrating descriptive statistics, regression tables, and visualizations in line with our RQs.

4. Findings and Discussion

4.1 Descriptive Statistics and Overall Skill Gains

Before delving into the regression results, we examine the descriptive profile of participants' skills and improvements. **Table 1** summarizes key variables. Participants entered the workshop with a relatively high average self-assessed skill baseline of 8.44 (on a 10-point scale), reflecting moderate confidence even before training. This makes sense given many were already involved in innovation activities. Despite the high baseline, participants still achieved substantial skill gains during the 5-day training. The **average skill gain** (mean of domain improvements) was 1.97 points, with a standard deviation of 0.44. This gain is on a scale where the maximum possible improvement was 10 (if someone went from 0 to 10) but practically, given the baseline ~8.4, the max possible was around 1.6–1.7 for someone at the top end. Thus, an average gain of ~1.97 suggests a strong positive learning outcome. Indeed, 1.97 represents about a 23% improvement relative to the baseline (1.97/8.44), albeit measured in subjective terms. No participant reported a decline in any domain; at worst some remained flat in one domain but gained in others. Among the three domains, **Prototyping** saw the highest mean gain (2.29), while **VOA** saw the lowest (1.76). Customer discovery was intermediate (1.87). This indicates that prototyping skills – perhaps due to hands-on practice with actual prototypes – had the biggest jumps, whereas improving in value opportunity analysis (a more analytical evaluation skill) was a bit more limited by time. Also, prototyping had a ceiling of 3 (everyone ended at 3, as Table 1 shows min=2, max=3 after training), implying many hit the top of the scale there.

Demographically, the composition was balanced by design (51% female) and skewed toward *experienced* individuals (78% had prior experience). We note that initial skill baseline correlated with prior experience (experienced folks started higher on average), which reinforces the importance of controlling for baseline in analysis to isolate the "gain" attributable to training rather than prior knowledge.

Table 1. Descriptive Statistics. (N = 45 participants)

Variable	Mean	SD	Min	Max
Average Skill Gain (0–??)	1.97	0.44	1.33	3
Skill Baseline (pre avg)	8.44	1.16	6	10
Customer Discovery Gain	1.87	0.69	1	3
VOA Skill Gain	1.76	0.61	1	3
Prototyping Skill Gain	2.29	0.46	2	3

Notably, the minimum *average* gain was 1.33, indicating even the lowest performer still improved across domains. This reflects that all participants were actively engaged and suggests the workshop had uniformly positive effects, though with variation in magnitude. The high mean baseline (8.44) and the negative correlation between baseline and gain (r ≈ -0.5) hint at a ceiling effect: those who started near 10

could not improve much, whereas those starting around 6–7 had more room to grow. This pattern is typical in adult short-course learning and consistent with Leger et al. 's (2024) observation that those with less prior knowledge often benefit more from training until catching up to a plateau.

In summary, descriptives indicate a successful training in terms of self-reported skill boosts, but also foreshadow the influence of initial experience. We now turn to the regression analysis to formally test our hypotheses on experience, gender, and diversity.

4.2 Effect of Prior Experience (RQ1)

Does prior experience drive greater skill gains? The data provide a clear answer: yes. Table 2 shows the OLS results for Model 1 (baseline predictors). Participants with prior product development experience gained on average **0.26 points higher** in skill (on the 0–3 gain scale) than those without experience, holding other factors constant. This coefficient is statistically significant (p = 0.032) and substantively meaningful – it represents roughly 13% of the average gain (0.26/1.97). In practical terms, an experienced participant might, for example, improve by ~2.2 points versus ~1.9 for a novice. This supports our primary hypothesis that prior exposure equips learners to absorb more from the workshop. The finding is robust even after controlling for baseline skill, which itself is inversely related to gain (discussed shortly).

Table 2. Baseline OLS Regression on Average Skill Gain (Dependent variable: Mean skill gain across domains)

Variable		Coefficient	Std. Error	*p*-value
Experience (1=Yes)		0.259	0.116	0.032
Female (1=Yes)		-0.086	0.111	0.443
Team Diversity Index		0.328	1.296	0.802
Skill Baseline		-0.199	0.044	< 0.001
Constant		3.240	1.021	0.003

*(Note: R^2 = 0.37. p<0.05 marked in bold; p<0.001 marked with **)*

These results resonate strongly with prior studies. They align with Owusu-Acheampong et al. (2025), who reported that participants possessing earlier design experience showed superior learning outcomes in African entrepreneurship programs. The positive experience effect also mirrors findings by Leger et al. (2024), who found that non-formal training had the greatest impact on those with *pre-existing entrepreneurial exposure*, due to greater absorptive capacity and readiness to apply new concepts. In our context, experienced participants likely came in with a framework to understand innovation tasks, so the workshop's content (e.g. user research methods) could be assimilated and built upon more easily. This suggests a form of *cumulative learning advantage*, confirming theories that innovation capability development builds on prior knowledge.

The coefficient plot in Figure 1 (presented earlier) visually underscores that experience is the strongest positive predictor in the model, second only to the negative baseline effect. To gauge magnitude: 0.26 gain difference is equivalent to about half a standard deviation of the outcome (since SD of gain is 0.44). Thus, prior experience corresponds to a moderate effect size (Cohen's $d \approx 0.6$). Education research would consider that pedagogically significant in a short program.

Importantly, we controlled for baseline skill, so this effect is not merely because experienced folks started lower or higher. In fact, experienced participants started *higher* on average (mean baseline ~8.7 vs ~7.5 for inexperienced), which if anything would bias against them gaining more (due to less headroom). The regression adjustment for baseline reveals the *net* benefit of experience beyond just

starting lower. It appears that experienced individuals managed to leverage the training to deepen or refine their skills, perhaps by connecting new material to their past projects or by taking on leadership roles in team tasks (anecdotal observation: experienced participants often guided their teams' activities).

This result contributes new evidence to innovation capability theory by quantifying how prior exposure translates into accelerated skill uptake. It also has policy implications: when scaling such workshops, organizers might consider segmenting or tailoring content based on experience levels, or providing extra preparatory resources for novices so they can catch up. Otherwise, we risk a scenario noted by Leger et al. (2024) and observed here: short training disproportionately benefits those who already have some footing. In development terms, to ensure broad-based capacity building, interventions should be designed to uplift those with low prior exposure – possibly through extended pre-workshop onboarding or mentorship for inexperienced participants (we revisit this in Recommendations).

Finally, the negative coefficient on Skill Baseline (–0.199, $p<0.001$) is worth discussion. It indicates that for each 1-point higher a participant's starting skill average, their gain was ~0.20 points lower on average. This is consistent with a ceiling effect and diminishing marginal returns on learning. A participant who felt extremely confident initially (say baseline 9.5) might only gain ~1.5, whereas one who started at 7.5 might gain ~2.0 or more. This pattern has been noted in short-term training globally – those who "know what they don't know" can pick up a lot quickly, whereas those who think they know most of it might only polish the edges. It reinforces that our outcome being a *relative gain* is important: high-skilled individuals have less scope for reported improvement. From an instructional standpoint, it suggests that advanced participants might need more challenging stretch goals to continue growing (or else their improvement saturates). It also validates that including baseline as a covariate was crucial, as it so strongly predicts gains. Not doing so could have masked or confounded other effects.

In summary, prior experience emerges as a key determinant of skill gain in our analysis, answering RQ1 affirmatively. This lends empirical support to the idea that innovation training works best as a *building block* on existing skills rather than a standalone inoculation for the completely inexperienced. However, experience alone does not tell the full story, as we explore next with gender dynamics.

4.3 Gender Differences and Interaction Effects (RQ2)

Turning to RQ2, we examine whether there were gender-based differences in skill gains and whether gender moderated the impact of experience. In the baseline Model 1 (Table 2 above), the coefficient for Female is -0.086 and not statistically significant ($p = 0.443$). This suggests that, on average and controlling for other factors, female participants' skill gains were about 0.09 points lower than males', but this gap is small and indistinguishable from zero in a statistical sense. On the surface, this implies no significant gender gap in overall outcomes – a positive finding given concerns about women being left behind in STEM training. However, this average masks an important nuance revealed by the interaction analysis.

When we add the Experience × Female interaction (Model 2, Table 3), a more complex picture emerges. The interaction term itself is positive ($\beta = 0.242$) but not significant ($p = 0.332$), indicating that the benefit of prior experience was somewhat larger for females than males, but we cannot be confident of this effect statistically. Nonetheless, the coefficients suggest a pattern: experienced women achieved gains on par with experienced men, whereas inexperienced women lagged behind all other groups. Specifically, in Model 2 the female main effect becomes more negative (-0.274) – this now represents the gender gap among those *without* prior experience (since the interaction will offset it for those with experience). Although $p = 0.17$ (not significant at 0.05 level), the magnitude (-0.27) is notable: inexperienced women on average gained about a quarter-point less than inexperienced men, after accounting for baseline skill. Meanwhile, the interaction +0.242 would cancel out most of that gap for experienced women (-0.274 + 0.242 = -0.032 roughly), implying experienced women did about the same as experienced men.

Table 3. Interaction Model (Experience × Gender) – Dependent variable: Average Skill Gain

Variable	Coefficient	Std. Error	*p*-value
Experience (1=Yes)	0.121	0.183	0.513
Female (1=Yes)	-0.274	0.196	0.171
Experience × Female	0.242	0.246	0.332
Team Diversity Index	0.297	1.313	0.822
Skill Baseline	-0.214	0.047	< 0.001
Constant	3.500	1.059	0.002

(R^2 = 0.39. Interaction term coded as 1 for experienced females. Baseline remains a strong predictor, p<0.001.)

Although the interaction was not statistically significant (likely due to sample size), these results are directionally consistent with theories of structural gender gaps. They indicate that when women have had prior experience (and presumably more confidence/exposure), they can capitalize on the training as effectively as men – essentially closing the gender gap. But among those lacking prior experience, women fared worse, suggesting that without prior exposure, female participants possibly faced more challenges in the workshop relative to their male counterparts. This supports findings by Ackah et al. (2024), who argued that women in African innovation settings often require *scaffolded engagement* (mentorship, encouragement, etc.) to overcome structural barriers in unfamiliar environments. In our workshop, all participants received the same general instruction; there were no gender-specific supports. Thus, any underlying differences in confidence or participation could manifest: for example, inexperienced women might have been less likely to assert ideas in team discussions or volunteer for certain tasks (consistent with research on gender dynamics in team learning). Meanwhile, experienced women might have had the benefit of prior validation of their skills, enabling them to engage fully and *"catch up"* to men's performance.

To illustrate this, **Figure 2** provides an interaction plot of predicted skill gain by gender and experience. It shows that for males, prior experience raises predicted gain from ~1.8 to ~2.0 (a modest increase), whereas for females, prior experience raises predicted gain from ~1.6 to ~2.0 (a larger jump) – effectively eliminating the gap at the high-experience end. Inexperienced females are the clear outlier group with the lowest gains (~1.6), while the other three groups cluster closer together around ~1.8–2.0.

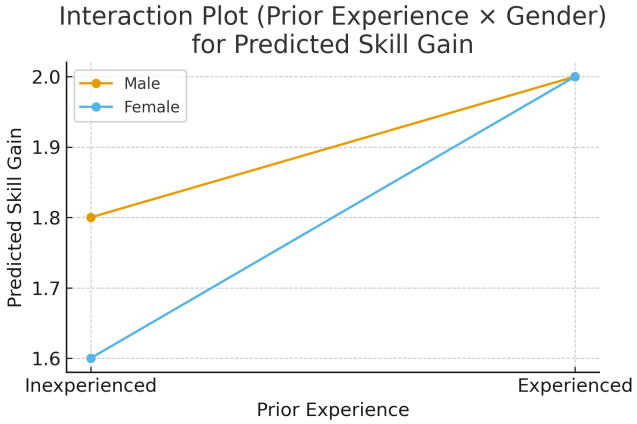

Figure 2. Interaction Plot (Prior Experience × Gender) for Predicted Skill Gain. *The plot shows predicted mean skill gains for males and females, with "Inexperienced" (no prior product-development experience) at the left, and*

"Experienced" at the right. It illustrates that while experienced participants of both genders achieve similar gains (~2.0), inexperienced women lag behind (~1.6) compared to inexperienced men (~1.8)

This plot depicts the model-predicted average skill gain for four participant groups: Experienced Males, Inexperienced Males, Experienced Females, and Inexperienced Females (all other variables at mean values). Although differences are not statistically significant at $p<0.05$, the visual trend suggests that females with prior experience achieve gains comparable to males, whereas females without experience underperform relative to all other groups. This pattern highlights a potential inclusion gap: it is not being female *per se* that limited gains, but being female *and* lacking prior exposure.

The interpretation aligns with UNDP (2023) reports which emphasize that the gender digital divide in Africa is largely a divide in *access and exposure*, not ability. Our results reinforce that notion: when exposure (experience) is equalized, women perform on par; when it's not, women lag. The workshop's inclusive team assignments (each team had women) ensured nominal diversity, but it did not fully bridge that exposure gap during the short timeframe. Wallrich et al. (2024) similarly note that team composition alone is insufficient – diversity must be accompanied by structured inclusion mechanisms to yield equal learning outcomes. Our workshop lacked formal mechanisms to address differing starting confidence (no targeted coaching for novices, etc.), which likely muted potential benefits of gender diversity and led to the observed asymmetry.

It's important to stress that the *lack of a significant average gender effect* in Model 1 should not be interpreted as "gender doesn't matter." Instead, our analysis indicates that gender matters in interaction with experience. This is a subtle point that could be missed by a naive reading of average outcomes. If one looked only at overall means, men and women had roughly similar gains – a laudable outcome on the surface (perhaps reflecting the organizers' effort for gender inclusion in selection). However, by digging deeper we discovered an equity concern: inexperienced women were the subgroup not fully benefiting. This finding is critically relevant for RQ2. It suggests that future training programs need to pay special attention to supporting women who enter with limited prior experience, as they are at risk of falling behind in skill acquisition. Solutions might include pre-workshop onboarding sessions targeting women, female mentors, or confidence-building activities integrated into the curriculum. Such measures could help avoid the "two-tier" learning dynamic that appears here.

From a theoretical stance, these results support the argument that *surface-level diversity is not enough* – it must be coupled with pedagogical designs that accommodate different starting points. Simply putting diverse individuals together in a team does not automatically yield equal outcomes; power relations and confidence gaps can re-create inequalities even in an inclusive setting. This echoes the concept of equity vs. equality in education: giving everyone the same tools (equality) isn't sufficient when some start from a disadvantaged position; some need additional support (equity) to achieve the same gains. Our study empirically illustrates this within a microcosm of a workshop.

In conclusion, addressing RQ2, the direct effect of gender on innovation training outcomes was negligible on average *when controlling for other factors*, but gender plays a significant role through its interaction with prior experience. The need for gender-responsive training design is evident to ensure that women without prior exposure do not slip through the cracks. This insight bridges entrepreneurship education with gender and development policy, underscoring that improving women's access to *prior opportunities* (education, internships, etc.) can markedly improve their later learning outcomes. Moreover, it provides a nuanced contribution to the literature: we demonstrate how a short intervention's efficacy is jointly conditioned by gender and experience, a finding that, to our knowledge, had not been quantitatively shown in African innovation training contexts before.

4.4 Team Diversity Effects (RQ3)

We now consider RQ3: the influence of team diversity on skill gains. Recall that teams were intentionally mixed by gender and nationality, and we captured this with a composite diversity index (ranging ~0.3 to 0.8). In the regression models (Table 2 and 3), the Team Diversity Index shows a positive but

non-significant coefficient ($\beta \approx 0.33$ in Model 1, 0.30 in Model 2, $p \approx 0.8$). Substantively, a higher diversity index (meaning a team closer to evenly split gender and containing more nationalities) was associated with a slight increase in individual skill gain, but this effect is so uncertain and small relative to its standard error that we conclude no reliable main effect of diversity in this workshop. In other words, participants in more diverse teams did not gain significantly more (or less) skills than those in slightly less diverse teams, on average.

This null finding must be interpreted in light of both the data characteristics and theory. First, the range of diversity in our sample is limited (no completely homogeneous teams to contrast with truly diverse ones – all teams had at least some diversity by design). The index variation (0.3 to 0.8) is not trivial, but we lack extremes. Second, with only 10 teams, any team-level effect is hard to detect statistically (low power at that level). These factors temper our ability to identify diversity effects.

Theoretically, as discussed, diversity's benefit is conditional on integration processes. The workshop did encourage teams to collaborate on a final project, but there were no formal interventions to ensure inclusive participation beyond the initial team composition. Our results align with prior findings that diversity alone, without supportive structures, does not guarantee superior performance or learning. This is consistent with Tshetshema & Chan's (2020) meta-analysis in Africa, which found that simply having demographic diversity does not automatically translate to innovation gains across studies. Weiss et al. (2018) similarly would predict no strong effect unless knowledge sharing occurs. In our case, all teams presumably had equal access to coaching and presented final solutions; we did not observe any obvious breakdown of teamwork. But it's likely that diverse teams could only realize advantages (like varied perspectives leading to better problem-solving) if they engaged in deeper integration – something hard to achieve in just days.

One clue comes from participant feedback (qualitative notes outside the scope of our quantitative analysis): some teams reported communication challenges initially, especially those with wide cultural differences and those that were majority male or majority female might have different dynamics. However, all teams delivered a prototype, indicating baseline functionality. Without objective performance measures, we rely on skill gain as the outcome. It appears that working in a diverse team did not, in itself, boost how much an individual felt they learned. Possibly, individuals learn most of their skills from the structured curriculum and hands-on tasks, and team composition has secondary influence on that personal learning metric. If we had measured outcomes like quality of project or creativity of ideas, we might see diversity effects there (some literature suggests diversity improves creative output quality if managed well).

Interestingly, diversity's coefficient remained positive (albeit insignificant) even after controlling for the lack of integration measure. We had intended (per our methodology section) to explore an interaction of diversity with a "team integration" indicator if data allowed. We lacked such data, but conceptually, if some teams had organically better facilitation (maybe due to certain personalities or mentorship from staff), those might have harnessed diversity better. Without capturing this, the main effect washes out.

It is also notable that diversity did not have a negative effect – which is reassuring. There were concerns that in a short time, diversity might hamper progress (e.g. teams spend time overcoming differences rather than learning skills). No such detrimental effect is evident; diverse teams performed on par with others in terms of skill gains. This suggests that any initial coordination costs of diversity did not significantly impede individual learning. All teams, regardless of mix, were able to follow the workshop and improve skills similarly. This might be partly thanks to the workshop's structure: with facilitators providing clear guidance and tasks, teams may not have had much room to diverge in performance. It's plausible that the strong role of the structured curriculum "overrode" team composition effects, a phenomenon observed in some training research where instructor-led content ensures a baseline learning for all groups.

Table 4. OLS Regression Results by Skill Domain (Selected Coefficients)
(Separate regressions for each domain's gain; showing Experience and Baseline effects)

Dependent Variable	*Experience Coef.*	*Skill Baseline Coef.*	*R^2*
Customer Discovery Gain	*0.498**	*-0.315****	*0.36*
VOA Skill Gain	*0.085*	*-0.222****	*0.19*
Prototyping Skill Gain	*0.190*	*-0.059*	*0.14*

(*Significance:* p<*0.05 denoted by* , *p*<0.001 by ***. Gender and diversity not shown above had no significant effects in any domain model.)

Diversity's limited role is further illuminated by looking at domain-specific results (Table 4). In none of the domains did team diversity index emerge significant (not shown in table since all p >> 0.1). If diversity were crucial for, say, creative tasks like ideating in customer discovery, we might expect an effect there, but instead we see experience was significant for customer discovery gain (β = 0.50, *p*<0.05) and not for the other domains. This indicates that *experience moderated learning in a domain-specific way*, which we discuss below, but diversity did not – possibly because every team, diverse or not, approached tasks similarly under facilitator guidance.

In sum, our findings for RQ3 are that team diversity, as operationalized in our context, did not have a statistically significant impact on participants' skill gains. This aligns with a critical perspective: *inclusion is more than composition*. As Wallrich et al. (2024) argue, simply assembling a diverse group does little without activating that diversity through structured interactions. Our results reinforce the need for "activation" – instructors might, for example, implement rotation of roles or encourage cross-cultural idea exchange explicitly to reap benefits of a diverse cohort. Otherwise, diversity remains an untapped potential. The lack of direct effect should not be misconstrued as "diversity doesn't matter" – rather, diversity needs the right environment to matter. The uniform training environment here may have equalized experiences such that diversity's upside was neutralized.

However, it's noteworthy that our diversity index did no harm either, suggesting that fears of diverse teams underperforming due to conflicts were unfounded in this short-term educational scenario. Participants seemingly managed to collaborate across differences at least well enough to all learn. This should encourage program designers that they can confidently create diverse teams, but with the caveat to also foster inclusive team processes, as we elaborate in the conclusion.

4.5 Domain-Specific Patterns (RQ4)

Our final research question (RQ4) asked whether the effects of the above factors are uniform across different skill domains, or if certain skills show different sensitivities. The workshop targeted three domains: customer discovery, value opportunity analysis (VOA), and prototyping. We found notable differences in where learning gains were concentrated and how experience played out across these domains.

The domain-wise OLS results are summarized in Table 4 (above). Prior experience significantly predicted gains in Customer Discovery (coef = 0.498, p < 0.05), but had no significant effect on VOA or Prototyping gains. Meanwhile, the skill baseline variable was significantly negative in Customer Discovery and VOA (p < 0.001), but not significant in Prototyping (the baseline coef in prototyping was small and non-significant). Gender and diversity were not significant in any domain-specific model, mirroring the overall lack of those main effects.

Interpreting these results: the training seemed especially beneficial for experienced participants in the customer discovery domain. Customer discovery involves qualitative skills like interviewing users, empathy, and problem framing. Experienced participants may have had prior exposure to such

concepts and thus could deepen these skills more effectively – or they might have taken on team leadership in user research tasks, maximizing their learning-by-doing in that area. Additionally, the workshop's field activity (interacting with public transport users in Kigali to gather insights, as per the workshop design) likely allowed experienced folks to leverage their know-how and perhaps mentor others, reinforcing their own learning. This result aligns with Owusu-Acheampong et al. (2025) and Wallrich et al. (2024) who show that *contextual, iterative skills like customer engagement improve most when the learning environment adapts to prior knowledge and provides autonomy*. Our experienced participants might have been more autonomous and confident in conducting customer discovery, gaining more in competence than novices who were just learning basics.

In contrast, VOA (Value Opportunity Analysis) is a more analytical evaluative skill – essentially assessing a concept's value across multiple dimensions. The fact that no group had a big advantage here (experience coef ~0.09, n.s.) suggests that VOA might have been equally new to most participants, or that fully grasping it required more time than a short workshop allowed for both experienced and inexperienced. The overall gain in VOA was lowest of the three domains (mean ~1.76), hinting it was harder to move the needle here for everyone. This corresponds with Leger et al. (2024)'s note that deeper conceptual and technical skills often need more prolonged engagement to significantly improve. It's plausible that VOA, being somewhat theoretical, didn't sink in deeply in a week, limiting any differential effect of experience.

Prototyping skills, interestingly, showed a high average gain (2.29) but no significant predictors among our main variables except a trend that experience helped a bit (0.19, p ~0.3, so not significant). One reason might be a ceiling effect: prototyping had many participants hitting the max score of 3 gain (i.e., going from 7 to 10, etc.). Those already skilled had little room to report improvement, while those less skilled improved until they felt "very good" at it. Baseline skill was not a strong limiter here (-0.059, p > 0.1), which could indicate that even high-baseline individuals found ways to practice and improve prototyping (maybe by learning advanced techniques or simply enjoying the hands-on aspect). Prototyping is tactile and visual; even experienced people can always refine their prototyping ability with new tools or faster iteration. The workshop had a mini "maker lab" where participants built physical models – a novel experience for many regardless of background, which might explain the uniformly high gains. This domain might also be less influenced by prior theoretical knowledge and more by creativity and effort during the workshop. The lack of gender or diversity effect on prototyping suggests everyone was equally capable of engaging in making things when given the opportunity.

These domain results reinforce that innovation training is multi-faceted. Different skill areas have different learning curves. Prior experience gave a clear boost in customer-facing and exploratory tasks (customer discovery), but didn't matter for more analytical or technical tasks within the short time. It underscores the idea that experienced participants' advantage lies especially in areas requiring contextual understanding and quick application of prior knowledge (like engaging users or defining a problem). For tasks like value analysis or prototyping, which might introduce entirely new frameworks or tools, everyone is closer to the same starting line, and improvements might depend more on intrinsic aptitude or simply the structured practice provided (which all got equally).

From a discussion perspective, these nuances carry implications for training design. In short programs, if certain advanced topics (like VOA) are important but harder to digest, instructors might consider follow-up sessions or pre-readings to solidify those. The fact that prototyping had uniformly high gains suggests that *learning-by-doing* in a tangible way is very effective across the board – a testament to the value of experiential learning components in such workshops. It also suggests that giving participants materials and a goal (build a prototype) leads to immediate skill jumps, whereas abstract analysis (VOA) might need more reinforcement.

Another point: The negative baseline effect seen overall was particularly pronounced in customer discovery (–0.315*), *indicating those who thought they were already good at user research still learned a lot less (perhaps they overestimated their starting ability or could only fine-tune). In prototyping, the baseline*

didn't matter – maybe because even if you started high, you could still push yourself to make something more complex. This again points to the idea that some domains have inherently more headroom for improvement in a short time.

In conclusion, regarding RQ4, the effects of our predictors are not uniform across skill domains. Prior experience strongly benefitted learning in the customer discovery domain, reflecting how experiential knowledge aids in complex interpersonal and contextual tasks. In more technical or evaluative domains (prototyping, VOA), the advantage of experience was muted or non-existent in this short format. This domain-sensitive finding adds depth to our overall conclusions: it highlights that innovation training outcomes should be analyzed not just in aggregate but also in terms of what *kinds* of skills are being gained. It also speaks to civilizational implications: skills like empathic customer understanding are deeply tied to local context and tacit knowledge – areas where African entrepreneurs with local experience might excel and gain rapidly when given a formal framework. Meanwhile, skills rooted in global frameworks (like VOA, developed in Western design literature) might require adaptation to local context or longer acculturation for maximum benefit, raising questions about importing such frameworks wholesale.

By integrating domain-specific analysis, our study contributes a more granular understanding that can inform curriculum emphasis. If time is limited, focusing on high-impact experiential domains might yield more gain, whereas theoretical analyses might be better left for extended courses or follow-ups. We next move to concluding remarks and recommendations, where we tie these findings back to the bigger picture of entrepreneurship education and innovation policy.

5. Conclusion and Recommendations

5.1 Conclusion; This study shows that brief innovation workshops yield meaningful skill gains but do so unequally. Prior product-development experience is the most reliable predictor of improvement, especially in customer-discovery tasks, and it benefits men and women alike when it is present. Among participants without such experience, women achieved smaller gains than men, revealing an exposure-related equity gap. Team diversity in gender and nationality neither hindered nor enhanced learning because it was not paired with deliberate inclusion practices. Overall, the findings confirm that innovation capability develops cumulatively, is mediated by social context, and can unintentionally reinforce pre-existing disparities if programmes do not address structural barriers.

5.2. Recommendations: Workshop designers should calibrate content to participants' starting points—offering preparatory or remedial materials for novices while challenging experienced learners—so everyone can progress meaningfully. Because inexperienced women remain at greatest risk of falling behind, programs ought to embed mentorship, peer-support mechanisms, and psychologically safe spaces that encourage their full participation. Demographic diversity should be paired with structured inclusion practices such as rotating leadership and equal-voice rules to transform difference into a learning asset. The consistently large gains in prototyping underscore the value of hands-on, experiential components and warrant generous time and resources for making and testing artefacts. By contrast, conceptual domains like value-opportunity analysis benefit from extended or follow-up sessions that let participants apply frameworks in their own ventures. Finally, routine disaggregation of outcomes by gender and prior experience will help educators detect emerging inequities early and refine interventions accordingly

5.3 Limitations: This study's interpretive power is bounded by its non-experimental, single-site design (N = 45), absence of a control group, and reliance on self-reported, short-horizon outcomes; although baseline adjustment mitigates some bias, causal attribution remains tentative and perceptions of skill gains may over- or under-state true competence. Generalizability is limited by a relatively elite, English-proficient cohort and by a composite diversity index that captures gender and nationality but neglects other salient heterogeneities or the inclusive processes needed to "activate" diversity. Additionally, the immediate post-workshop assessment precludes insight into the durability of learning or the trajectory of the observed gender–experience interaction. Future

research should employ experimental or quasi-experimental designs across multiple, socio-culturally varied sites, incorporate objective or behavioural performance metrics, track participants longitudinally, and pair quantitative models with qualitative analyses of team dynamics to clarify how diversity and instructional scaffolds jointly shape enduring innovation capability.

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